Detection of Congestive Heart Failure Using Discrete Wavelets Transform of Heart Rate Variability Signals

Alia S. Khaled, Mohamed I. Owis, Abdalla S. A. Mohamed

Department of Systems and Biomedical Engineering, Faculty of Engineering, Cairo University, Cairo, Egypt

Abstract—**The analysis of heart rate variability (HRV) signals gives an indirect measure of heart health, as defined by the degree of balance between sympathetic and vagus nerve activity and the effect of this balance on heart rhythm. In this paper, discrete wavelets transform (DWT) is used to analyze HRV signals in order to detect congestive heart failure (CHF). Interpolation is needed as a preprocessing step, and principal component analysis (PCA) is applied on wavelets coefficients to reduce them before application of classifiers. Results have shown that a good promise for an automatic detection of CHF signals using Bayes minimum-error classifier, voting k-nearest neighbor classifier and back propagation neural networks especially after normalizing wavelets coefficients used in classification.**

Keywords— **HRV, CHF, DWT, PCA, Back propagation Neural Networks**

I. INTRODUCTION

Congestive heart failure is not a disease but is a common and serious condition or process, in which the heart is unable to pump enough blood to meet the needs of the body's tissues. The heart doesn't "fail" in the sense of ceasing to beat (as occurs during a heart attack). Rather, it weakens, usually over the course of months or years, so that it is unable to pump out all the blood that enters its chambers. As a result, fluids tend to build up in the lungs and tissues, causing congestion (hence the name "congestive" heart failure). Early diagnosis of CHF is required especially it usually develops slowly. This slow onset and progression of CHF is caused by heart's own efforts to deal with its gradual weakening. Heart tries to make up for this weakening by enlarging and by forcing itself to pump faster to move more blood through the body.

ECG test cannot diagnose heart failure, but it is simple and painless to perform and can indicate other heart problems. The major benefit of an ECG is to help in determining patients who most likely do not need more accurate (but more expensive) diagnostic tests. In this study, ECG signal is used to detect heart failure. It can be done by extracting HRV signal from a given ECG signal.

HRV has been the subject of numerous clinical studies investigating a wide spectrum of cardiac and non-cardiac diseases and clinical conditions, such as: myocardial infarction (MI) [1, 2], sudden cardiac death and ventricular arrhythmias [3, 4, 5], Hypertension [6, 7], Diabetes mellitus [8, 9, 10], and Heart transplantation [11, 12, 13, 14].

Our objective here is to detect the CHF using HRV signals. The detection problem is divided into three stages: preprocessing, feature extraction and classification. In the preprocessing stage, HRV signals are interpolated in order to generate RR time-series from the RR interval tachograms. The extraction of the descriptive features is taking place in the second stage using discrete wavelets transform (DWT). Coming to the classification stage, statistical classifiers are used to detect the presence of the CHF such as Bayes minimum-error classifier, and voting k-nearest neighbor (k-NN) classifier. Back propagation neural networks are also used for the same purpose.

II. PREPROCESSING AND FEATURE EXTRACTION

In this section, the preprocessing and feature extraction stages are discussed.

A. Preprocessing

The HRV signal is derived by measurement of the time interval between successive R-R events. When defined in this way, the HRV signal is equidistantly sampled in terms of R-R intervals not time, and may be processed by methods that require equidistant samples. It is important to note that when we speak of the spectral content of such a signal, we are speaking of the interval power spectra and not the conventional power spectra of a time-sampled process. In this study, we adopt the approach outlined by DeBoer [15], in which it is possible to map the interval spectra to time or frequency by mapping the R-R events to the time axis, separated by time intervals equivalent to the average heart rate. With this approximation, the frequencies of other physiological processes (i.e. breathing) can be located in the interval spectrum.

Since average heart rate is different from signal to another in the data set used, so RR time series is irregularly time-sampled and need to be interpolated prior to spectrum estimation [16].

Interpolation is a method of constructing new data points from a discrete set of known data points. Given a sequence of n distinct numbers x_k called nodes and for each x_k a second number y_k, we are looking for a function f so that

$$f(x_k) = y_k, k = 1,....., n \tag{1}$$

A pair x_k, y_k is called a data point and f is called the interpolant for the data points. Here, “Piecewise Cubic Hermite Polynomial Interpolation” is used at rate of 4 Hz. This method preserves monotonicity and the shape of the data.

B. Discrete Wavelets Transform

Wavelet analysis is a windowing technique with variable-sized regions. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information (high-scale), and shorter regions where we want high-frequency information (low-scale). Calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates an awful lot of data. If only a subset of scales and positions are chosen, then the analysis will be much more efficient and just as accurate. Such an analysis can be obtained from the discrete wavelet transform (DWT).

For many signals, the low-frequency content is the most important part. It is what gives the signal its identity. The high-frequency content, on the other hand, imparts flavor or nuance. In wavelet analysis, we often speak of approximations and details. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components. The original signal passes through two complementary filters and emerges as two signals. The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree.

Since the analysis process is iterative, in theory it can be continued indefinitely. In reality, the decomposition can proceed only until the individual details consist of a single sample [17]. In practice, a suitable number of levels can be selected based on the nature of the signal. In the present work, the frequency range of the HRV signal is from 0 to 0.4 Hz, and then the original signal would be decomposed until the cut-off frequency of the low-pass filter becomes ≥ 0.4 Hz. db4 is used in this work with two-level decomposition to achieve a cut-off frequency of 0.538 Hz at the low-pass filter.

When applying DWT on the available signals and extracting the coefficients as features to be used in the detection of CHF, it is found that there are a large number of coefficients (273 coefficients) that are needed to be reduced. In order to do that, principal component analysis (PCA) is used as a dimensionality reduction method.

C. Principal Component Analysis (PCA)

Principal component analysis is analogous to Fourier analysis in that the data is described in terms of the coefficients of a predetermined orthogonal set. But rather than using sines and cosines, the orthogonal set is chosen so that it describes the samples from studying most population efficiently, with the smallest number of terms. Principal component analysis is an efficient technique for dimensionality reduction in multivariate statistical analysis. Multivariate statistical analysis deals with the analysis of the data that consist of measurements on a number of individuals or objects [18]. PCA derives the direction of a set of orthogonal vectors that point into the direction of the highest variance of the data set. The principal components (PCs) are calculated as the eigenvectors of the covariance matrix of the data set. The eigenvalues denote the variance that corresponding PCs (i.e. eigenvectors) account for.

D. Normalization

The effect of normalization of all parameter values in the features vector within a fixed range around the zero (e.g., between ± 1) is studied as a possible convenient preprocessing step for proper weighting of parameters used in the classification [19, 20]. The normalized parameter is calculated using equation (2).

$$
\begin{aligned}
&\mathit{Normalized\,Parameter} = \\
&\frac{2 * (\mathit{OriginalParameter} - \min)}{(\max - \min)} - 1
\end{aligned}
\tag{2}
$$

III. CLASSIFICATION

In order to investigate the performance of the proposed features in detecting the CHF, we attempt to implement some of the most commonly used classifiers and use them to perform this task. Two statistical classifiers and back propagation neural network classifier are used.

The performance of the algorithms is reported in terms of sensitivity, specificity, positive predictive accuracy, and error rate. These values are standard statistics used to measure the performance of the classification algorithms [21]. Sensitivity measures how well the algorithm can identify CHF signals, specificity measures how well the algorithm identifies the signal NOT in CHF, positive predictive accuracy measures how often the algorithm is correct when it calls a signal CHF, and error rate is a single value summary of the overall percentage of mistakes made by the algorithm.

A. Statistical Classifiers

Statistical classifiers can be divided into parametric and non-parametric techniques. Parametric statistical pattern recognition uses given or assumed information about the prior probabilities to obtain the classification [22]. On the other hand, the non-parametric approach does not require any a priori information about the probability distributions of the data in each class; classification is performed based on the provided data samples with known class membership [19]. The statistical classifiers used are:

1) *Bayes Minimum-Error Classifier:* The Bayes decision rule classifies an observation (i.e., a test sample) to the class that has the higher a posteriori probability among the two classes [19]. In this study, the data set is assumed to have a Gaussian conditional density function and the a priori probabilities are assumed to be equal for the two types (normal and CHF).

2) Voting k-Nearest Neighbor (k-NN) classifier: This technique is non-parametric and assigns a test sample to the class of the majority of its k-neighbors [19].

B. Back propagation Neural Networks

In the present work, "Resilient Back propagation" training algorithm was used. Multilayer networks typically use sigmoid transfer functions in the hidden layers. Here, this network is used with 2 neurons in hidden layer, 2 neurons in the output layer, and number of neurons in the input layer is variable according to the features vector length. The network is trained to output a 1 in the correct position of the output vector and to fill the rest of the output vector with 0's. If the input is the features of normal signal then the output will be 1 in the first neuron and 0 in the second and vise versa.

IV. RESULTS

A. Data Collection

The HRV signals used in this work were obtained from PhysioBank [23]. The normal signals were obtained from "Normal Sinus Rhythm RR Interval Database" and "The MIT-BIH Normal Sinus Rhythm Database", while CHF signals were obtained from "Congestive Heart Failure RR Interval Database" and "The BIDMC Congestive Heart Failure Database". HRV signals were driven from ECG signals using annotation files.

Since in the present work we used short-term HRV signals (2-5 min), the extraction of short-term HRV signals from the overall of 106 long-term signals (from all databases) is needed. So the data set used consists of 600 short-term HRV signals divided to: 400 for design (learning) subset as 200 for normal signals and 200 for CHF signals, and 200 for test subset as 100 for normal signals and 100 for CHF signals.

Learning and testing subsets are fixed for different classifiers to neutralize their effect on results [19].

B. Feature Extraction

The 273 wavelets coefficients extracted using DWT are needed to be reduced using PCA. In this work, we choose number of principal components (PCs) to be 30 to achieve efficiency of 95.53 %.

C. Classification Results

The specificity (spec.), sensitivity (sens.), positive predictive accuracy (+ve pred.) and error rate (err.) results of applying the classifiers on wavelets coefficients before and after normalization are shown in tables 1 to 4.

V. DISCUSSION

It is obvious from classification results that normalizing of the feature vectors has been shown to improve the overall accuracy, indicating its importance as a preprocessing step.

The results of applying Bayes minimum-error classifier, voting k-nearest neighbor classifier and back propagation neural networks have shown a high level of accuracy when using normalized features.

VI. CONCLUSION

DWT is used with HRV signals to detect CHF. First, the signals are needed to be interpolated to form regular RR time series. Then application of DWT takes place followed by a dimensionality reduction method (PCA) to reduce the number of wavelets coefficients from 273 to 30 coefficients. These coefficients are normalized before entered to classification stage.

Finally classification is done using Bayes Minimum-Error Classifier, Voting k-Nearest Neighbor Classifier, and Back propagation Neural Networks.

TABLE 1
BAYES MINIMUM-ERROR CLASSIFIER

	Before Normalization	After Normalization
Sensitivity	8.20%	92.90%
Specificity	87.60%	94.40%
Positive Predictive Accuracy	39.81%	94.31%
Error Rate	52.10%	6.35%

TABLE 2
VOTING K-NN CLASSIFIER

k	Before Normalization				After Normalization			
	Sens.	Spec.	+ve Pred.	Err.	Sens.	Spec.	+ve Pred.	Err.
1	55.50%	70.40%	61.27%	37.05%	99.50%	100.00%	99.50%	0.25%
2	76.40%	84.90%	78.25%	19.35%	100.00%	100.00%	100.00%	0.00%
3	54.70%	72.80%	61.64%	36.25%	100.00%	100.00%	100.00%	0.00%
4	68.20%	83.00%	72.30%	24.40%	100.00%	100.00%	100.00%	0.00%
5	55.90%	73.40%	62.47%	35.35%	100.00%	100.00%	100.00%	0.00%
6	64.50%	80.60%	69.42%	27.45%	100.00%	100.00%	100.00%	0.00%
7	57.10%	73.80%	63.24%	34.55%	100.00%	100.00%	100.00%	0.00%
8	63.30%	79.60%	68.44%	28.55%	100.00%	100.00%	100.00%	0.00%
9	57.80%	74.60%	63.87%	33.80%	100.00%	100.00%	100.00%	0.00%

TABLE 3
VOTING K-NN CLASSIFIER INCONCLUSIVE RATES

k	Before Normalization		After Normalization	
	Normal	CHF	Normal	CHF
1	0.00%	0.00%	0.00%	0.00%
2	42.40%	31.70%	0.50%	0.00%
3	0.00%	0.00%	0.00%	0.00%
4	24.60%	22.40%	0.00%	0.00%
5	0.00%	0.00%	0.00%	0.00%
6	16.10%	14.80%	0.00%	0.00%
7	0.00%	0.00%	0.00%	0.00%
8	11.50%	11.40%	0.00%	0.00%
9	0.00%	0.00%	0.00%	0.00%

TABLE 4
BACKPROPAGATION NEURAL NETWORKS

	Before Normalization	After Normalization
Sensitivity	68.00%	99.90%
Specificity	56.50%	99.80%
Positive Predictive Accuracy	60.98%	99.80%
Error Rate	37.75%	0.15%

According to results, it is concluded that wavelets coefficients are capable of representing the normal and CHF signals. In addition, normalization of the feature vectors before classification has a great effect in improving the detection accuracy.

REFERENCES

[1] Kleiger RE, Miller JP, Bigger JT Jr, Moss AJ, for the Multicenter Post-Infarction Research Group, "*Decreased heart rate variability and its association with increased mortality after acute myocardial infarction*," Am J Cardiol, 1987

[2] Casolo GC, Stroder P, Signorini C, Calzolari F, Zucchini M, Balli E, Sulla A, Lazzerini S., "*Heart rate variability during the acute phase of myocardial infarction,*" Circulation, 1992

[3] Hisako Tsuji, MD; Martin G. Larson, ScD; Ferdinand J. Venditti, Jr, MD; Emily S. Manders, BS; Jane C. Evans, MPH; Charles L. Feldman, ScD; Daniel Levy, MD, "*Impact of Reduced Heart Rate Variability on Risk for Cardiac Events*," The Framingham Heart Study Circulation.;94:2850-2855 , 1996

[4] P.K. Stein, PhD and R.E. Kleiger, MD, "*Insights from the study of Heart Rate Variability*," Annu. Rev. Med., 50:249-261, 1999

[5] Jacqueline M. Dekker, PhD; Richard S. Crow, MD; Aaron R. Folsom, MD, MPH; Peter J. Hannan, MStat; Duanping Liao, MD, PhD; Cees A. Swenne, PhD; Evert G. Schouten, MD, PhD, "*Low Heart Rate Variability in a 2-Minute Rhythm Strip Predicts Risk of Coronary Heart Disease and Mortality From Several Causes*," The ARIC Study, PubMed, 2000.

[6] Mussalo H, Vanninen E, Ikaheimo R, Laitinen T, Laakso M, Lansimies E, Hartikainen J., "*Heart rate variability and its determinants in patients with severe or mild essential hypertension*," Clin Physiol.,21(5):594-604, 2001

[7] Raymond B, Taverner D, Nandagopal D, Mazumdar J. Australas, "*Classification of heart rate variability in patients with mild hypertension*," Phys Eng Sci Med , 0(4):207-13, 1997

[8] Risk M, Bril V, Broadbridge C, Cohen A., "Heart rate variability measurement in diabetic neuropathy: review of methods. Diabetes," Technol Ther, 3(1):63-76, 2001

[9] Pagani M., "*Heart rate variability and autonomic diabetic neuropathy*," Diabetes Nutr Metab, 13(6):341-6, 2000

[10] Lanting P, Faes TJ, Heimans JJ, ten Voorde BJ, Nauta JJ, Rompelman O., "*Spectral analysis of spontaneous heart rate variation in diabetic patients*," Diabet Med, 7(8):705-10, 1990

[11] Sands KE, Appel ML, Lilly LS, Schoen FJ, Mudge GH Jr, Cohen RJ., "*Power spectrum analysis of heart rate variability in human cardiac transplant recipients*," Circulation ;79(1):76-82, 1989

[12] Ramaekers D, Ector H, Vanhaecke J, van Cleemput J, van de Werf F, "*Heart rate variability after cardiac transplantation in humans*," Pacing Clin Electrophysiol,19(12 Pt 1):2112-9, 1996

[13] Binder T, Frey B, Porenta G, Heinz G, Wutte M, Kreiner G, Gossinger H, Schmidinger H, Pacher R, Weber H., "*Prognostic value of heart rate variability in patients awaiting cardiac transplantation*," Pacing Clin Electrophysiol, 15(11 Pt 2):2215-20, 1992

[14] Beckers, F., Ramaekers, D., van Cleemput, J., Droogne, W., Vanhaecke, J., Van de Werf, F., Aubert, AE., "*Association between restoration of autonomic modulation in the native sinus node and haemodynamic improvement after cardiac transplantation*," Transplantation, 2002

[15] R. W. DeBoer, J. M. Karemaker, and J. Strackee, "Comparing the spectra of a series of point events particularly for heart rate variability data," IEEE Trans. Biomed. Eng., vol. BME-31, no. 4, pp. 384-387, 1984.

[16] Juha-Pekka Niskanen, Mika P. Tarvainen, Perttu O. Ranta-aho, and Pasi A. Karjalainen, "Software for advanced HRV analysis," Report No. 2/2002, University of Kuopio, Department of Applied Physics, Finland

[17] S. Mallat, "A theory for multiresolution signal decomposition: the wavelet representation," IEEE Pattern Anal. and Machine Intell., vol. 11, no. 7, pp. 674-693, 1989

[18] J.J. Gerbrands, "On the relationships between SVD, KLT, and PCA," Pattern Recognition, vol. 14, Nos. 1-6, pp. 375-381, 1981.

[19] Yasser M. Kadah, aly A. Farag, Jacek M. Zurada, Ahmed M. Badawi, and Abou-Bakr M. Youssef, "*Classification Algorithms for Quantitative Tissue Characterization of Diffuse Liver Disease from Ultrasound Images*," IEEE Transactions on Medical Imaging, vol. 15, No. 4, 1996.

[20] H. L. van Trees, "*Detection, Estimation, and Modulation Theory*," Pl. I. New York: Wiley, 1968.

[21] Brian Young, Don Brodnick, and Randy Spaulding, "*A Comparative Study of a Hidden Markov Model Detector For Atrial Fibrilation*," IEEE, 1999.

[22] K. Fukunaga, "*Introduction to Statistical Pattern Recognition*," 2nd ed. New York: Academic, 1990.

[23] *PhsioBank*, Physiologic Signal Archives for Biomedical Research", http://www.physionet.org (Accessed April 2006)